LCA Data Quality

Multi-User Test of the Data Quality Matrix for Product Life Cycle Inventory Data

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Abstract

The data quality matrix for product life cycle inventory data proposed in WEIDEMA & WESNAES (J. Cleaner Prod. (1996), 4: 167-174) was subjected to a multi-user test, in which 7 persons scored the same 10 datasets representing 10 different processes. Deviations among scores were listed, and the causes for deviations were determined and grouped into a limited number of well-defined classes. For the majority of the scores, the different test persons arrived at the same score. Deviations occur most often among neighbouring scores. Only a smaller number of the deviations (less than 10% of all scores) affect the overall assessment of the data quality and/or uncertainty of the corresponding dataset. Based on the analysis of the causes of the deviations, improvements to the matrix and its accompanying explanations were suggested and implemented (reported in the appendix to this paper). The average time consumption for the scoring by the different test persons was less than 10 minutes per data set. It is concluded that the time consumption and the number of deviating scores can be kept at an acceptable level for the pedigree matrix to be recommended for internal data quality management and for comprehensive communication of quality assessments of large amounts of data.

Keywords: Data quality, multi-user test, LCA; Life Cycle Assessment (LCA), data quality, multi-user test; multi-user test, data quality, LCA

1 Introduction

A data quality matrix for product life cycle inventory data was originally proposed in WEIDEMA (1994). As a result of discussions in the LCA Working Group on Inventory Enhancement (Sub-group on Data Handling) under the Society of Environmental Toxicology and Chemistry, an improved version of the matrix was presented to the 2nd SETAC World Congress in Vancouver in 1995, and published in the Journal of Cleaner Production (WEIDEMA & WESNAES, 1996). A third and further improved version of the matrix is presented in the appendix to this paper. Several authors have reported successful application of the matrix to specific studies or application areas (KUSKO & HUNT, 1996; LABOUZE & ROEDERER, 1996; STRÖMBERG et al., 1997; VAN DER VEN, 1997). Some of these authors suggested modifications to the matrix when applied to specific uses. For example, for use in the pulp and paper industry, STRÖMBERG et al. (1997) suggested a more sensitive indicator for temporal correlation (with only one year between each score as opposed to the 3, 6, 10, and 15 years in the original matrix).

However, such modifications for specific applications will make comparisons between different studies more difficult, and would thus work against one of the main objectives of using the matrix, namely the easy communication of the data quality assessment. The matrix was designed to be generally applicable for all types of processes in all sectors of society. However, the subsequent interpretation of the resulting score depends on the type of process, the industrial sector, the purpose of the life cycle assessment, and the importance of the process within the specific life cycle. For example, a score 2 on "Geographical correlation" could well be acceptable for process types with little geographical variation, while it would be unacceptable for processes with large variation (e.g. agricultural processes, which are very climate dependent). Likewise, a score 2 on "Temporal correlation" could be regarded as problematic in very rapidly developing sectors (e.g. the electronics and pulp and paper industry), while it would not give rise to concern in other sectors. The demands for data quality can vary between life cycle assessments with different purposes (assessments that are used publicly to differentiate competing products will place larger demands than assessments for internal use in a company) and between processes, depending on the importance of the process for the overall result. Therefore, since the same score will anyway be given different importance, we would therefore discourage modifications of the original matrix, when used for communication purposes.

WRISBERG et al. (1996) and LINDEIJER & VAN DEN BERG (1997) suggest aggregation of the indicators at system level and add two indicators on system completeness and reliability. Since the scores do not represent any "amount" of data quality (e.g. a score 2 for one indicator is not necessarily of the same importance as a score 2 on another indicator, nor is a score 4 necessarily twice as problematic as a score 2 on the same indicator), we would dissuade such aggregation of data quality indicators. In WEIDEMA & WESNAES (1996), we show that

an expression of reliability at the system level can be obtained by interpreting the data quality in terms of additional uncertainty and using Monte Carlo simulations of the analysed systems to give the uncertainty on the final result. By including estimates of missing data with proper data quality descriptors and uncertainty added, there is no need for additional indicators at the system level.

WRISBERG et al. (1996) and LINDEIJER & VAN DEN BERG (1997) have also suggested more radical modifications to the matrix. They include geographical correlation under the indicator on technology (a modification we would discourage, since the distinction has proven to be useful in practice), add an indicator on uncertainty (which we believe is better reported in its original form, as it is already a numerical value), split the completeness indicator into statistical representativeness and two indicators on missing data (due to cut-off and aggregation, respectively), and split the reliability indicator according to different verification issues (source, mass balance and allocation).

Although we acknowledge the added information value of a more detailed data quality index, we believe that the number of indicators should be kept as low as possible. Furthermore, our original proposal aimed at keeping interrelated issues together, thus also ensuring that the individual indicators can be seen as independent (an important prerequisite when using the indicators as basis for assigning additional uncertainty to the data). For example, an adequate validation procedure may improve the reliability of an estimate, otherwise regarded as having low reliability. This is our motivation for keeping the different measurement, calculation and verification issues together under the heading of "reliability of the source". A similar link between statistical representativeness and missing data was the motivation for keeping these issues together under the heading of "completeness". We believe our own matrix represents an adequate representation of the relevant issues with the lowest number of indicators.

Other authors have suggested simplifications to the matrix. For example, VAN DER VEN (1997) suggested only 3 scores for completeness (as opposed to 5 in the original matrix). In our opinion, such simplifications reduce the value of the information provided by the resulting data quality index. Furthermore, such simplifications do not appear to be warranted. The multi-user test reported in this paper was performed to investigate the reproducibility of the scores among different users as well as the time consumption for scoring. We believe that the results reported here demonstrate that simplifications of the data quality matrix are unnecessary.

2 Test Procedure and Results

The data quality matrix presented by WEIDEMA & WESNAES (1996) was subjected to a multi-user test in which seven persons independently of each other scored the same 10 datasets representing 10 different processes based on the information available in a public, electronic database (FREES & PEDERSEN, 1996). One test person scored only nine datasets, so the total number of independently scored datasets was 69. The test was carried out in two rounds, the first with four persons using the original data quality matrix, the second round with three persons using an improved version of the matrix, prepared on the basis of the experiences from the first round (this improved version is included as appendix to this paper).

The average time consumption for the scoring was 10 minutes, varying from 4 to 28 minutes for the individual data set. This time consumption is for the scoring only, not for finding the data in the database, nor for documenting the result of the scoring (since the data documentation should always be a part of a life cycle study anyway). If the three first scores for each person were removed to allow some time for learning, the average score was reduced to 8 minutes. Thus, it is reasonable to conclude that for an experienced person, the time used for scoring is likely to be between 5 and 10 minutes per dataset. This time consumption must be regarded as acceptable in view of the time usually devoted to data collection and documentation in general (budgeting rules applied by different consultants range from a minimum of 4 hours per data set up to several days when the data collection includes on-site visits). Several test persons expressed that they were positively surprised by how quick it was to use the matrix compared to how complicated it looked at first sight.

Since each dataset is scored on five independent indicators (see the appendix), the test resulted in 5 x 69 = 345 independent scores. At a meeting between the test persons of the first round, an agreed score was determined for each indicator in each dataset. Deviations from the agreed score were listed and the cause for the deviation was determined. In total 124 scores (36%) were determined as deviating from an agreed score. 80 of these (23%) were between neighbouring scores. Except for the temporal indicator, which had relatively few deviating scores, the deviations were distributed evenly among the indicators.

Table 1 contains an analysis of the causes for the deviations. The deviations were classified in four groups of approximately equal importance:

- Simple mistakes, admitted at a review by the test persons to be misprints (i.e. where the explanation given for the score was correct, but noted with a wrong corresponding number) or misinterpretations of the data in the database. Such mistakes would be caught in a review process.
- Mistakes which can be attributed to inadequate descriptions in the data quality matrix or its accompanying explanations. Such mistakes could be expected to be reduced or removed by reworking of the explanations. Examples of such mistakes are given in the Box.

- Mistakes caused by unclear information in the database. Most of the published environmental data on processes have very little information as to the quality of the presented data. For the test, we wished to use a publicly available database, where data quality information is presented in a detailed and structured manner. The selected database (FREES & PEDERSEN, 1996) was the one that – to our knowledge – fulfilled these criteria best. However, this does not mean that the presented data quality information was always adequate, as can be seen from Table 1. In the context of scoring according to the matrix, another problem occurred with this database, since it presents certain aspects of data quality as scores on a scale from 1 to 5, but based on different criteria than the data quality matrix to be used for the scoring. The mistakes, which can be attributed to the database, reflect the kind of mistakes that will always occur with secondary or literature data, which are seldom complete with regard to the way data quality is reported. However, when the matrix is used on primary data, collected by the same team which performs the scoring, this kind of mistakes are not likely to occur. Also, such mistakes could be avoided or reduced if the concepts and structure of the matrix had been used as a guideline when collecting and entering data into the database. This leaves us with a group of

- Deviations due to differences in interpretation among the test persons. It is noteworthy that out of the deviations in this class, nearly all were between two neighbouring scores (e.g. from 2 to 3, from 4 to 5, or *vice versa*). A small number of such small deviations are regarded as inevitable and not disturbing to the overall applicability of the matrix. The different indicators are not equally prone to such deviations. As expected, such deviations are nearly absent for the indicator "temporal correlation" where the distinction between two scores depends on a clearly defined numerical distance in years. Actually, nearly half the deviations (19 out of 40) are caused by the indicator "reliability", which should focus our attention on the possibility for improving the distinctiveness of the scoring criteria of this particular indicator. We found that "verification" could be described more clearly and with some examples (this has been done in the text in the appendix), while we did not find any possibilities to distinguish more clearly between a qualified and a non-qualified estimate although this distinction (between score 4 and 5) was the cause of more than half of the deviations on this indicator.

Table 1: Deviating scores classified according to cause

Cause of deviation	Number of deviating scores (out of 345)	Total for class
Simple mistakes which would be caught in a review process:		28 (8%)
Misprints	7	
Misinterpretations of data	21	
Mistakes which can be attributed to inadequate explanations to the matrix:		26 (8%)
Literal interpretation of scoring criteria	11	
Global data interpreted to have good correlation to unknown location in study	12	
Missing data not included in basis for score	3	
Mistakes caused by unclear information in the database:		30 (9%)
Interference from 5-point score in database	3	
Vague descriptions of source and data collection procedure	16	
Missing information on representativeness	9	
Data without year, but referred to as "modern"	2	
Deviations due to differences in interpretation:		40 (12%)
On reliability indicator	19	
On completeness indicator	8	
On temporal indicator	2	
On geography indicator	1	
On technology indicator	10	
Total	124	36%

Box: Examples of typical mistakes when applying the pedigree matrix

1. *Literal interpretation of scoring criteria*

The use of the pedigree matrix necessarily involves subjective judgement, which will depend on the background knowledge available to the person performing the scoring. Such subjective background knowledge should not be suppressed since it contributes to the correct assessment of the data at hand.

For example, if the data quality information for subterranean hard coal mining states: "The dataset represents 7 mines world-wide", a literal interpretation of the pedigree matrix would result in a score 5 on representativeness, since the representativeness is in principle unknown (the data set does not state the size of the population from which the 7 mines have been drawn). However, applying ones own background knowledge about how many mines exist will result in a more correct score of 1 or 2.

Similarly, if the time period for which the data set is valid is not specified in the data set, but it is specified which technology is used, a literal score of 5 for unknown temporal correlation may be wrong, if you actually know that the specified technology is new and introduced during the last 5 years (which would typically give a score of 2 on temporal correlation).

2. *Global data interpreted to have good correlation to unknown location in study*

Often, when the actual location and technology of the unit process under study is unknown, the desired data is average data. However, data of unknown geographical origin should still score 5 (for unknown) on the geographical indicator (rather than 1 or 2). Data of unknown geographical origin is not good quality data, just because the location of the process in the study is also unknown! A parallel argument could be made for data where the technology is unknown.

Weidema & Wesnaes (1996) have suggested that the data quality scores can be interpreted in terms of an additional uncertainty on the data, and showed that this uncertainty will typically be dominated by the data quality aspects with the highest indicator scores (representing the lowest quality). This means that out of the five scores for a data set, it will typically be one or two of the scores (those with the highest indicator score), which will dominate the overall uncertainty of the data set. This further implies that only deviations on these dominating indicators will be of importance. For example, if a dataset is already scoring 5 on two parameters, it is of little importance whether the remaining three scores are 1 or 4. Based on this insight, the individual, deviating scores were analysed. This showed that only 27 of the deviating scores (8% of all 345 scores) would be able to affect the resulting uncertainty assessment of the corresponding dataset.

In an attempt to reduce the number of deviating scores, improvements were made to the pedigree matrix and its accompanying explanations (see the improved text in the appendix). The improved matrix and explanations were used in the second, independent round of testing involving three new test persons with no prior knowledge of the matrix nor of the results from the first round. The result of this second round confirmed the conclusions from the first round, but contrary to our expectations, the mistakes that were assumed to be caused by inadequate explanations in the matrix, were still of the same magnitude as in the first round, despite the improved text. It may be argued that the matrix and its explanations may still be further improved to reduce such mistakes. At a meeting with the test persons from the second round, it was suggested that some examples of mistakes (e.g. the text from the **Box**) should be included in the explanations. It was not possible within the budget available for this study, to perform a third round to see if this would reduce the number of mistakes.

3 Conclusions

In two rounds, seven persons independently scoring the same 10 datasets, in most cases agreed on the scores to be given. Deviations occur most often among neighbouring scores. The causes for deviations can be described in a limited number of well-defined classes. Only a smaller part of the deviations (less than 10% of all scores) affect the overall assessment of the data quality and/or uncertainty of the corresponding dataset. Providing the scores are reviewed to catch misprints and misinterpretations, the number of deviating scores can be kept at an acceptable level. The time consumption for the scoring is less than 10 minutes per dataset, which is seen as acceptable.

Despite possible improvements to the data quality matrix and its explanations, there remains an irreducible amount of subjectivity in any data quality assessment. Thus, it should be emphasised that the scores should not be seen as objective, but rather as a representation of a subjective judgement of the data quality.

This does not compromise the usefulness of the pedigree matrix for internal data quality management and to communicate the subjective judgement of data quality in a comprehensive way. All the test persons confirmed their satisfaction with the usefulness of the pedigree matrix in respect to these purposes.

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Appendix: The Improved Matrix and Explanations

Formal data quality management starts with the definition of data quality goals and a data collection strategy as part of the definition of the goal and scope of the life cycle assessment. During data collection, data quality is documented for each set of data. The quality of the individual data sets may subsequently be related to the data quality goals through a number of data quality indicators, which specify the data quality in relation to the way it is used in the study. Thus, data quality indicators are used to judge the accordance between the specified data quality goals and the actual quality of the collected data. The purpose of this is to provide a data quality management tool, which makes it easy to survey the data quality and thereby to point at potentials for improving the data quality as well as to track sources of uncertainties.

Data quality indicators are semi-quantitative numbers attached to a data set, representing the quality of the data. The following data quality indicators are necessary and sufficient to describe those aspects of data quality, which influence the reliability of the result (→ *Table 2*):

The indicator **Reliability of source** describes the acquisition methods and verification procedures, which were used to obtain the data in question. Verification covers e.g. mass balances, repetitions, comparisons to earlier measurements or other data, and review by another person than the one responsible for the data acquisition. It is not possible to set strict rules for the degree of verification, which is required and adequate, since this depends on the type of data in question. However, it should be clear that as part of verification there is an element of independent control of the reliability of the data. Both literature data, calculated data, and data from production sites can vary from score 1 to 5, i.e. the score does not assess the type of source or origin as such, but indeed the reliability of the source. The indicator is independent of the data quality goals of the particular study: a decision made under the scope definition does not change the reliability of the data source.

The indicator **Completeness** describes whether parts of data are missing as well as the statistical representativeness of the data, i.e. whether the sample includes a sufficient number of data and whether the period is adequate to even out normal fluctuations. Missing parts of data are judged as more problematic (score 4 or 5) than missing representativeness (score 2 to 4). The missing data may possibly be isolated into an independent data set with its own data quality index, limiting the coverage of the remaining dataset, but improving its completeness within this area of coverage. As for the indicator Reliability of source, the indicator Completeness is independent of the data quality goals of the particular study.

The next three indicators all relate to the correlation between the data and the data quality goals concerning the technology or production conditions in a broad sense:

The indicator **Temporal correlation** expresses the degree of accordance between the year of the study (as stated in the data quality goals) and the year of collection of the obtained data. As technology develops very fast in some sectors of industry, 10 years difference between the year of study and the year of the data might cause the emissions and the production efficiency to be completely changed. Hence, the Temporal indicator is closely related to the data quality goals.

The indicator **Geographical correlation** expresses the degree of accordance between the production conditions (determined by both technical, natural geographical and societal circumstances) in the area relevant for the study (as stated in data quality goals) and in the geographical area covered by the obtained data. The production methods and the production conditions can be very different in Norway (e.g. small scale agriculture), USA (large scale productions, modern technology) and the East-European countries (older technology). These differences do not depend on geographical distance, but solely on differences in natural geography and societal conditions.

The indicator **Further technological correlation** concerns all other aspects of correlation than the temporal and geographical considerations. Although data may be of the desired age and representative of the desired geographical area, it may not be representative of the specific enterprises, processes or materials under study. Therefore, it can be necessary to use data from related processes or materials, which in some instances can be regarded as preferable to older data or data from a different geographical area.

To ensure a consistent use of the indicators, it is important that the 5 indicators are regarded as mutually independent. Obviously, data from a "wrong" area may imply that a different technology is used. Nevertheless, this aspect is described under Geographical correlation. The indicator Further technological correlation relates only to further differences occurring in spite of the data being of the same age and from the same geographical area.

Similarly, the indicator Completeness may indicate perfect representativeness even when the three correlation indicators show a very bad correlation. This is because the representativeness is not relating to the study in which the data is being used, but only to the data itself. A set of data may be completely representative of the U.K. situation in 1976, but still has a very bad correlation if the study is on French industry in 1995. Reversely, a perfectly fitting up-to-date set of data from the enterprise under study may not be complete.

The scores in the pedigree matrix are semi-quantitative. They serve as identification numbers only, and should not be regarded as representing a certain "amount" of data quality. Therefore, the numbers should not be compared across indicators (e.g. a score 2 for one indicator is not necessarily of the same importance as a score 2 on another indicator), nor should they be regarded as equidistant (e.g. a score 4 is not necessarily twice as problematic as a score 2 on the same indicator). For the same reason the numbers should not be added or in any other way aggregated.

The use of the data quality matrix will necessarily involve subjective judgements, which will depend on the background knowl-

Table 2: Data quality matrix with 5 data quality indicators (slightly revised after WEIDEMA, 1994)

Indicator score	1	2	3	4	5
Indicators, which are independent of the study in which the data are applied:					
Reliability of the source	Verified data based on measurements	Verified data partly based on assumptions or non-verified data based on measurements	Non-verified data partly based on assumptions	Qualified estimate (e.g. by industrial expert)	Non-qualified estimate or unknown origin
Completeness	Representative data from a sufficient sample of sites over an adequate period to even out normal fluctuations	Representative data from a smaller number of sites but for adequate periods	Representative data from an adequate number of sites but from shorter periods	Representative data but from a smaller number of sites and shorter periods or incomplete data from an adequate number of sites and periods	Representativeness unknown or incomplete data from a smaller number of sites and/or from shorter periods
Indicators relating to the technological and natural production conditions under which the data are valid, and therefore dependent of the data quality goals for the study in which the data are applied:					
Temporal correlation	Less than 3 years of difference to year of study	Less than 6 years of difference	Less than 10 years of difference	Less than 15 years of difference	Age of data unknown or more than 15 years of difference
Geographical correlation	Data from area under study	Average data from larger area in which the area under study is included	Data from area with similar production conditions	Data from area with slightly similar production conditions	Data from unknown area or area with very different production conditions
Further technological correlation	Data from enterprises, processes and materials under study	Data from processes and materials under study but from different enterprises	Data from processes and materials under study but from different technology	Data on related processes or materials but from same technology	Unknown technology or data on related processes or materials, but from different technology

edge of the person performing the scoring. For example, the data quality information in a study can be so lacking that it – with a literal interpretation – justifies a score 5 (data quality unknown), but if you know from your own background knowledge that for this process type it can never be less than a score 3 (e.g. for temporal correlation if the technology is recent), such background knowledge should be used when scoring. Thereby, you obtain the most correct score. When such background knowledge is applied more explicitly (thus deviating from a literal interpretation of the matrix), this background knowledge should be documented in an explanation for the score, else an expectation may be raised with the reader of the score, that the data quality is actually documented in the original data quality information for the process (in the example above, that the age of the data was actually stated).

Examples of determining data quality indicators

In a study on rye bread, the use of pesticides for Danish crops is reported as 2 kg active substance per hectare. Investigating the background of this data, we can determine its pedigree as (2,1,1,2,4). The explanation for this is shown below.

Similarly, the original data for the energy consumption for producing pesticides was 240 MJ/kg active substance. We may add the **qualifying pedigree** (3,1,5,3,4) which is determined below.

Listing data quality indicators for all data may improve the understanding of the typical problems in data quality of a particular study. This is very useful for improving the data collection strategy during a life cycle study.

The matrix in **Table 2** is intended for all types of processes in all sectors of society. However, the subsequent interpretation of the resulting score will depend on the type of process, the industrial sector, the purpose of the Life Cycle Assessment, and the importance of the process within the specific life cycle. For example, a score 2 on Geographical correlation could well be acceptable for process types with little geographical variation, while it would be unacceptable for processes with large variation (e.g. agricultural processes, which are very climate dependent). Likewise, a score 2 on Temporal correlation could be regarded as problematic in a very rapidly developing sector (e.g. the electronics industry), while it would not give rise to concern in other sectors. The demands for data quality can vary between Life Cycle Assessments with different purposes (assessments, which are to be used publicly to differentiate competing products will place larger demands than assessments for use internally in a company) and between processes, depending on the importance of the process for the overall result. Therefore, the same score will anyway be given different importance. In connection to the setting of the data quality goals for a Life Cycle Assessment, the processes should be classified according to the demands, which are placed on their data quality score.

Data quality indicator for amount of pesticides used	Score	Explanation
Reliability of source	2	The data source is the official Danish statistics, and their data is based on registrations from importers and manufacturers. The use in private gardens and the displacement of stock in trade over the years is not measured, but assumed to be negligible
Completeness	1	The data is determined for Denmark for the period 1988 to 1992. This is adequate to cover fluctuations over the years (agriculture conditions change with the weather and hence the years)
Temporal correlation	1	Data covers year of study
Geographical correlation	2	The data is an average for Denmark, not for the actual Danish farms supplying the ingredients for the rye bread
Further technological correlation	4	The data is an average for all Danish crops, not for the actual crops used as ingredients in the rye bread

Data quality indicator for energy for pesticide production	Score	Explanation
Reliability of source	3	The data source use computer calculations partly based on process descriptions in patent applications, not on measured data
Completeness	1	As such, the data is representative of the 39 pesticides mentioned in the source
Temporal correlation	5	The original data in the computer programme is from 1976, and based on older data (the data quality goal was 1992)
Geographical correlation	3	General data is applied to the specific pesticides used in Denmark. The production conditions for pesticides in different geographical areas are judged to be relatively similar with regard to energy consumption
Further technological correlation	4	An average of the 39 pesticides in the source is used for all pesticides used in the study